Fast Registration for Extreme Exposure Fusion

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Abstract

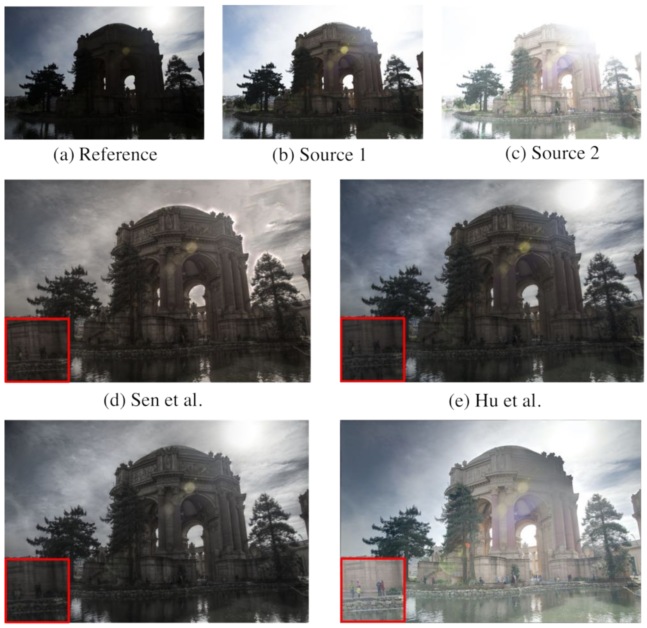
Image registration in high-dynamic range (HDR) synthesis based on multi-exposure image sequences is challenging. Camera motion and illumination change are the two most pressing issues. And as the scene illumination changes drastically and the camera movement increases, the result of feature extraction and filter matching gradually deteriorates. This will eventually lead to artifacts in the composite image. Unfortunately, existing methods can only deal with scenes with small differences in continuous exposure and a small amount of camera displacement. We propose an exposure registration algorithm that fills this void. We describe a powerful feature descriptor called wDoG, which guarantees high response regardless of overexposed/underexposed areas. The flow of the full registration is that the grid-cells are the smallest processing unit strategy and the prior rough estimation strategy is proposed, so that our algorithm finds a good compromise between computational complexity and registration quality. The experiments demonstrate our approach is extremely suitable for extreme HDR scenes with large exposure differences, where many mainstream algorithms are prone to fail.

In addition, with only two exposure low dynamic range (LDR) images with a 6-stop exposure gap, high-quality feature extraction and registration can be completed successfully and in less time than other registration algorithms, effectively preventing the artifacts.

Keywords: Image registration, grid-based partition, biologically inspired, illumination invariant, patch match.

We propose a method that fills the void of fast exposure registration algorithms. Our approach is applicable to both extreme exposure differences and displacements. Overall, our contributions are:

- A feature extraction framework (*wDoG*) based on illumination-insensitive joint multi-feature detection operators. The extraction framework can quickly detect extreme exposure scenes (especially underexposure) with extremely different exposures, which were previously difficult to handle, and is confirmed experimentally with a considerable amount of evenly distributed feature points.
- A grid-based corresponding neighborhood search matcher was designed. It only takes much less time than current algorithms to achieve image matching efficiently and stably.
- It is proved that when facing extreme exposure, high-quality multi-exposure image registration tasks can be successfully completed with fewer prerequisites, such as the number of LDR images, the range of exposure differences, whether there are large movements between image sequences, etc. It is also demonstrated that the algorithm has advantages in operating efficiency.



(a) Reference (b) Source 1 (c) Source 2

(d) Sen et al. (e) Hu et al.

(f) Gallo et al. (g) Ours**

Figure 1: Comparison with three state-of-the-art registration algorithms[1, 2, 3]. To produce a result that is visually comparable to the related work, we use the classic Laplace fusion algorithm[4] proposed by Burt et al. Due to the accuracy and quantity of feature points of our method, it presents clearer details. Images courtesy of Hu et al.[2] ** Our method uses only two exposures with a difference of 4 stops for registration as shown in (a) and (c).

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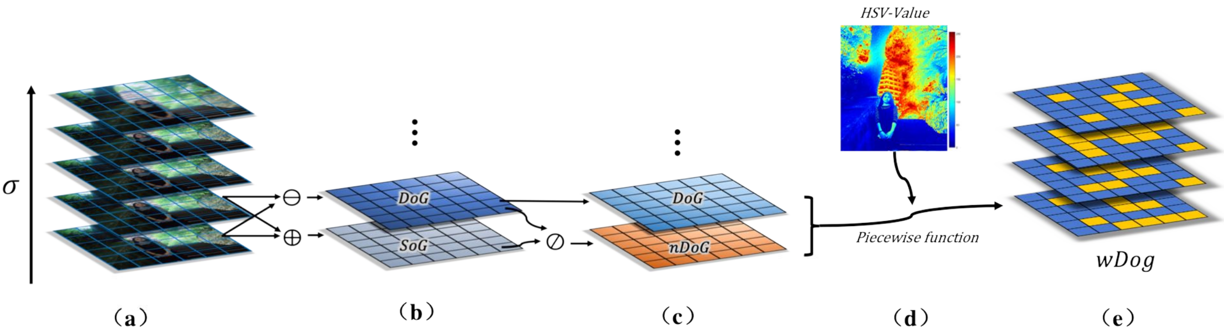


Figure 2: *wDoG* (Non-down-sampling image pyramid multi-feature joint detection framework) that not only combines the advantages of *DoG* and *nDoG* but also avoids their shortcomings. More specifically, the above framework cultivates the *nDoG*'s illumination variant in the underexposed image area as well as the original *DoG*'s excellent performance in the overexposed image area.

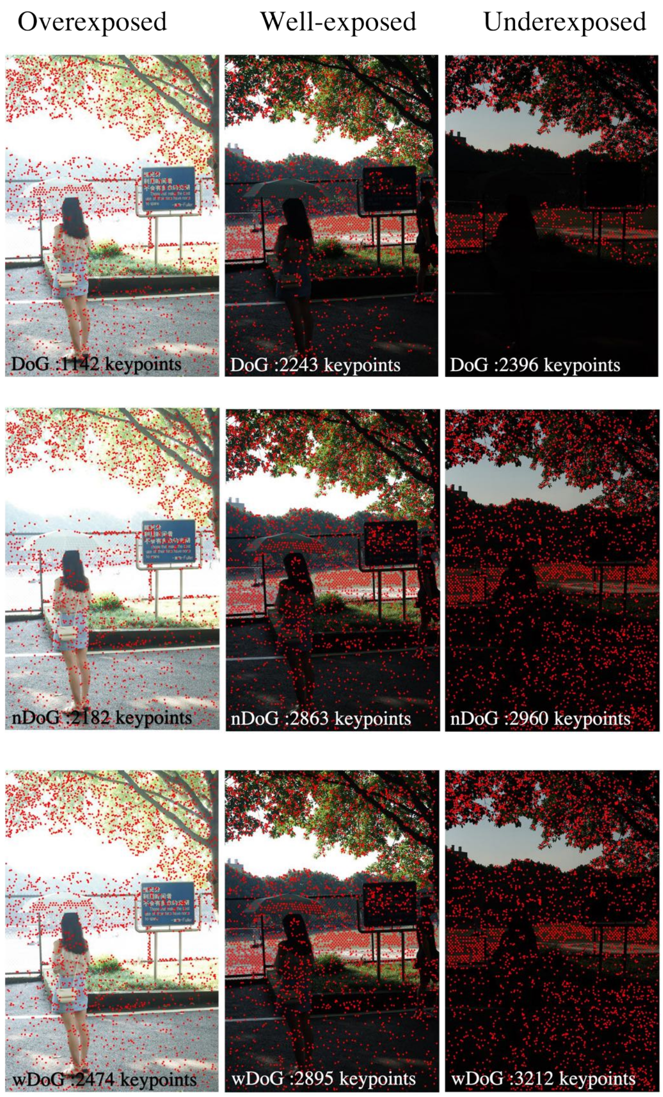


Figure 3: Comparison of the number of feature points in the three feature point detection frames of *DoG*, *nDoG*, and *wDoG* under different exposure scenarios.

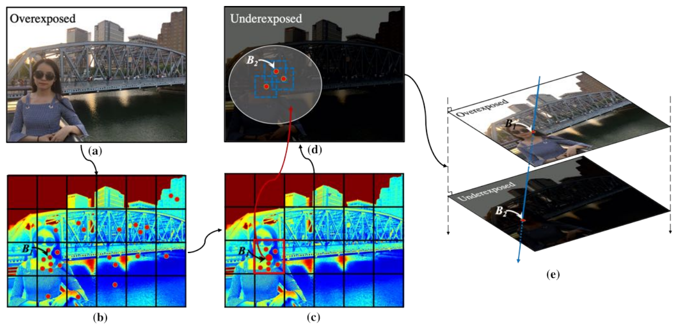


Figure 4: Flow of a priori coarse alignment algorithm. By using the prior information, the large displacement of the camera can be solved ingeniously, and the subsequent algorithms can be further accelerated.

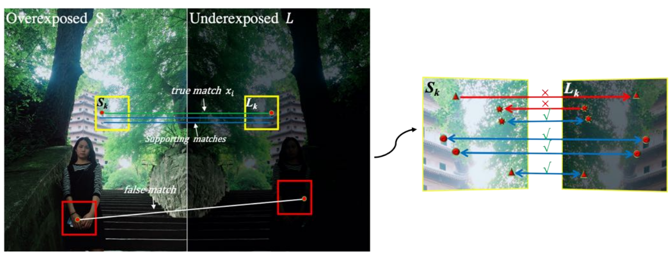
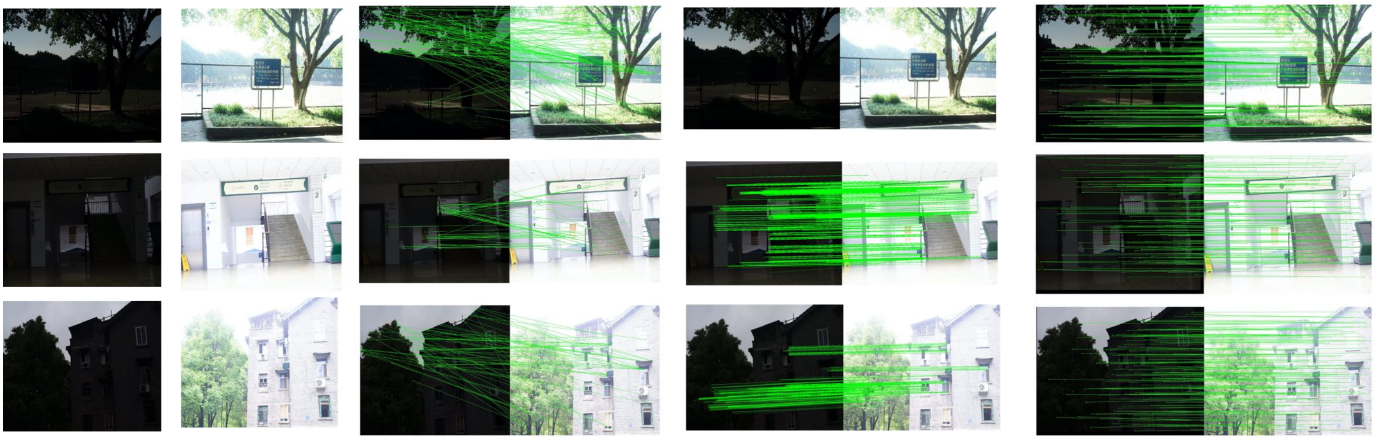
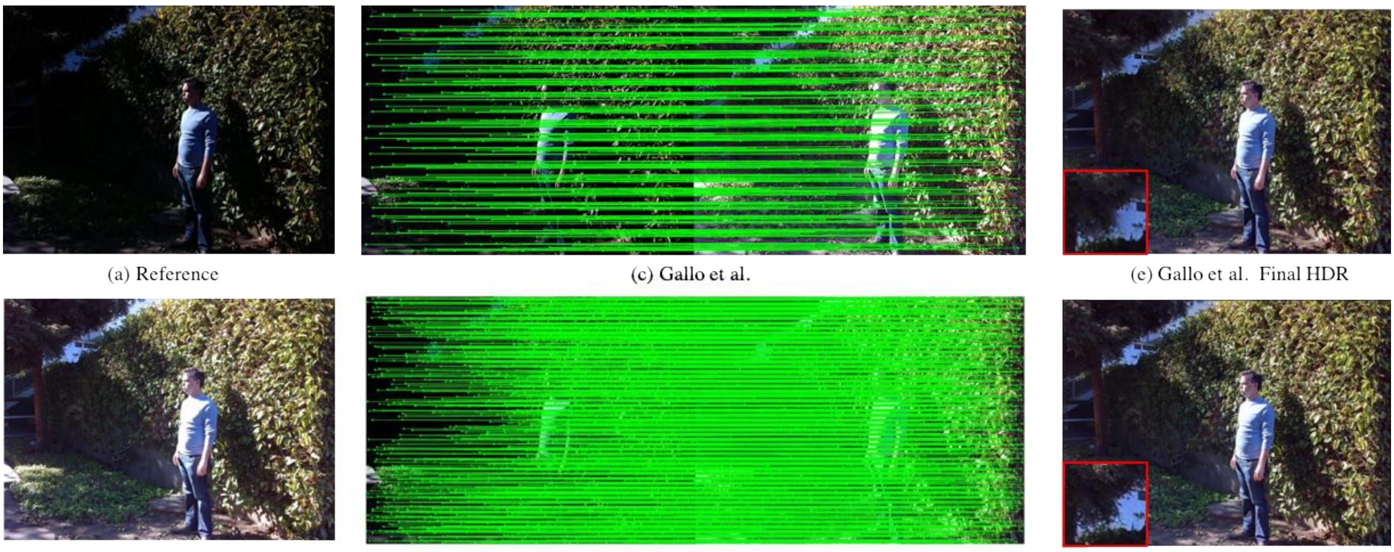


Figure 5: Our matching strategy further improves the accuracy of GMS[5] algorithm matching by introducing a two-way verification mechanism.



(a)Reference (b)Source (c)SIFT (d)GMS (e)Ours

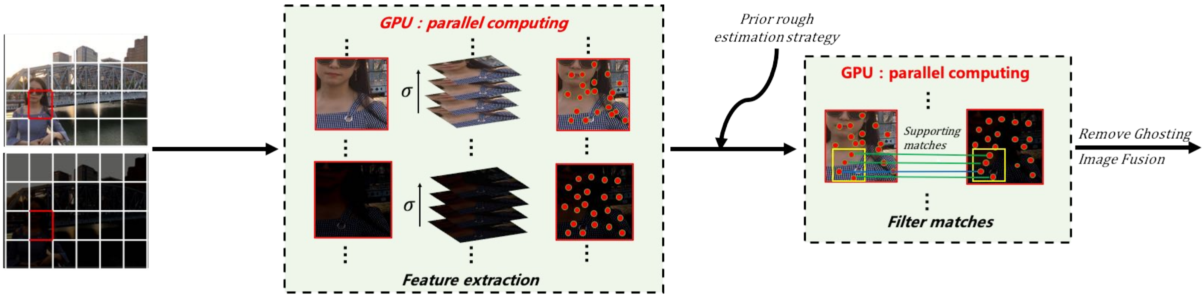
Figure 6: (c) It can be seen intuitively that the SIFT[6] matching results can only detect fewer feature points and have more mismatches when faced with an image sequence with a large exposure gap. (d) Although GMS[5] removes most of the mismatches, it also removes a large number of correct matching pairs and even no feature points are detected in the first scene. In addition, it can be clearly seen that the feature point distribution generated by GMS is extremely uneven. (e) It can be seen that our method does not have obvious mismatching pairs and preserves the correct matching pairs while producing a uniformly distributed set of feature points.



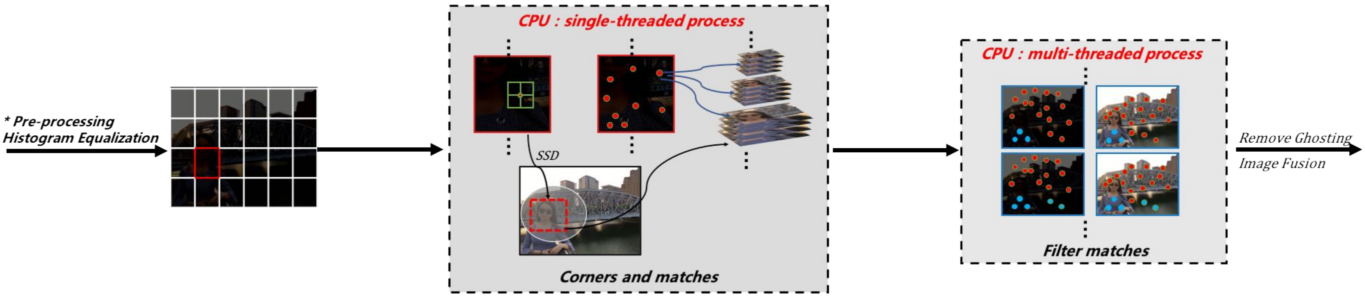
(a) Reference (c) Gallo et al. (e) Gallo et al. Final HDR

(b) Source (d) Ours (f) Ours Final HDR

Figure 7: Comparison with the method by Gallo et al.[3] Their results are similar to ours, with a uniform distribution of feature points; however, in terms of the number of matching pairs, it is suggested that our method's performance is better by comparing images (b) and (c). Similarly, images (e) and (f) show that there are some problems such as a sharp drop and loss of local details (note the artifacts around the leaves) in the final HDR image processed by Gallo et al. In addition, the two exposure LDR images provided by Gallo et al. differ only by 4 stops, whereas our method can generate a large number of correct matching pairs quickly when the exposures differ by 6 stops. Note that Gallo et al. perform histogram equalization to attenuate brightness differences.



(a) Our algorithm workflow.



(b) Gallo et al. algorithm workflow.

Figure 8: Comparison with the algorithm process by Gallo et al.[3]. (a) Show our algorithm flow. Thanks to our clever design, the whole process is based on the image grid with low data coupling. And it can make good use of GPU parallel computing acceleration. (b) Show the algorithm flow of Gallo et al. . Note that Gallo et al. preprocess the input image. They were fed images that were histogram equalized.

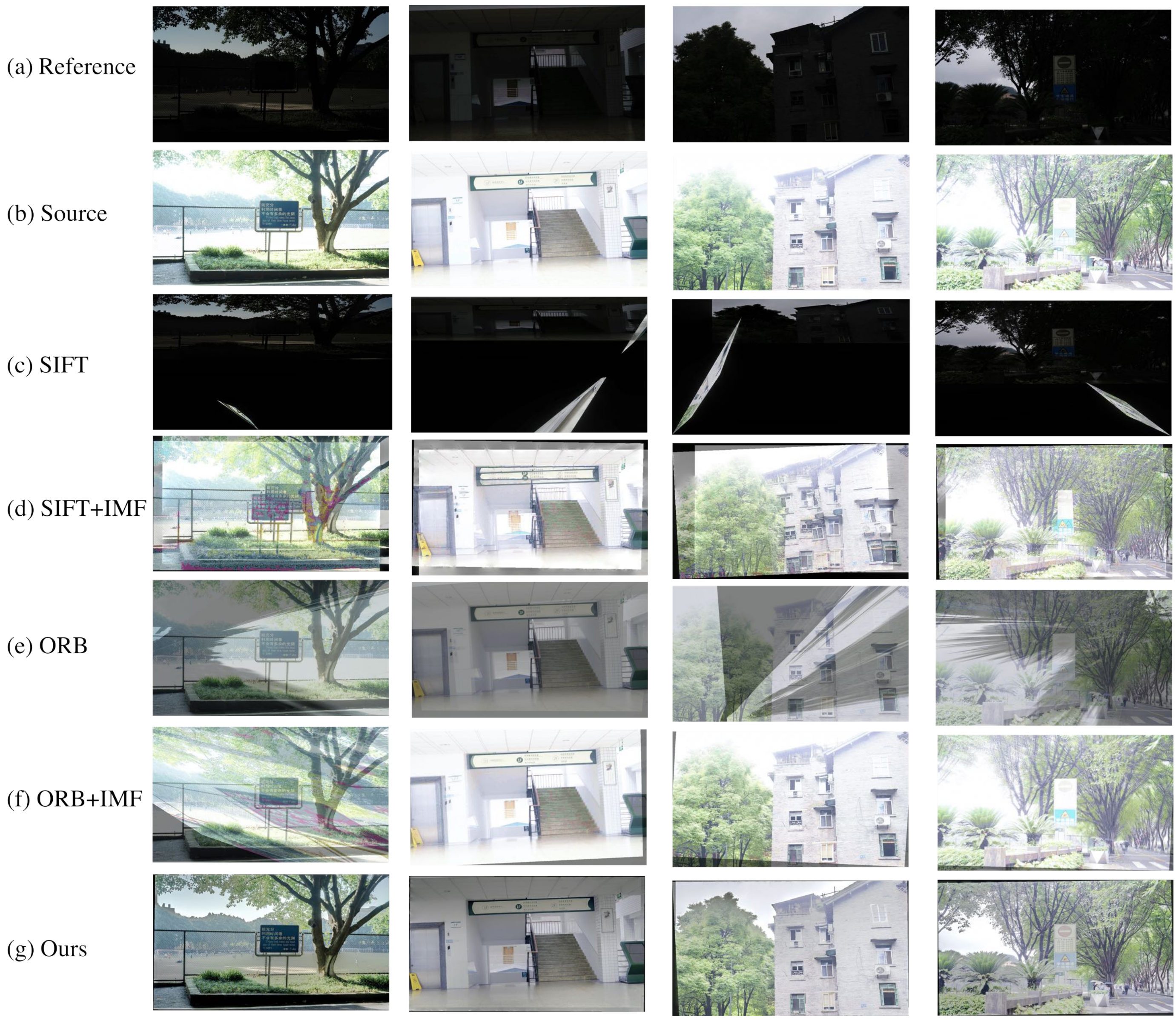
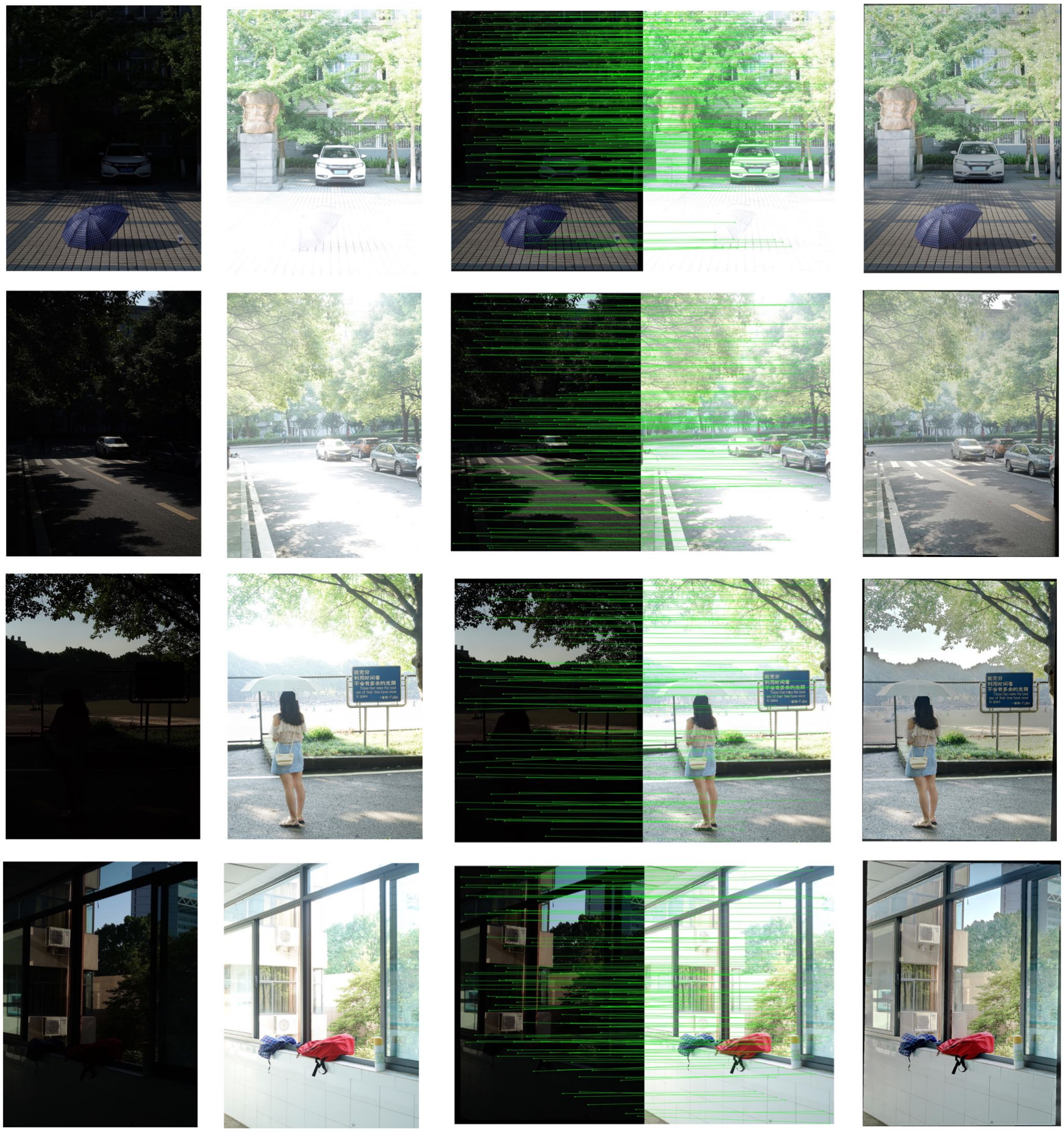


Figure 9: Some very challenging two-image stacks show that our method can be applied to a variety of scenes with different lighting conditions. Images (a) and (b) among the four scenes in the picture have a difference in exposure of 6 stops. It is impossible for algorithms using traditional feature point registration to complete the task under the conditions that only two images are provided. The results of direct fusion can directly reflect the accuracy of the feature points of each algorithm. In our method, images (g) exhibit better registration quality than (c), (d), (e), and (f). From a subjective viewpoint, it is very clear that the fusion results of other methods have many problems such as sharply reduced images, loss of local details, and large displacements and deformations. Although the fusion result shown in images (f) achieved some effects, there are still obvious displacements and texture blurs. Our method can extract matching pairs with high accuracy, strong robustness, and uniform distribution, and achieve the final fusion image with clear texture and no loss of details.



(a)Reference (b)Source (c) Ours matching result (d) Ours fusion result

Figure 10: Our method works well on a variety of extreme exposure difference scene. In (a) and (b) we show the input image with 6 levels of exposure difference. (c) show the uniform and considerable number of matching point pairs obtained by our algorithm. Finally, (d) show our fusion result through Laplace fusion algorithm[4].

References

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